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Research Article

An Integrated IoT and AI Monitoring System for Early Shrimp Disease Detection in Vietnam

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ABSTRACT

Introduction: Shrimp farming plays a crucial role in Vietnam's aquaculture industry, yet frequent disease outbreaks, primarily caused by poor water quality control, continue to present significant challenges and economic losses. To address this issue, this study proposes an Artificial Intelligence (AI)-enhanced Internet of Things (IoT)-based intelligent monitoring system aimed at improving shrimp health and promoting sustainable farming practices. Methods: The proposed system consists of an IoT framework that continuously monitors key water quality parameters, including pH, temperature, salinity, and dissolved oxygen using real time sensor networks, while pond-mounted cameras periodically acquire high-resolution images of shrimp. An AI-driven diagnostic model based on a transfer-learned ResNet-50 architecture analyzes these images to detect and classify diseases, including black spot disease, black gill disease, and white spot syndrome virus (WSSV), fusing its predictions with threshold-based anomaly detection in multiparameter sensor data. Results: Several algorithms were trained on the proposed four-class shrimp disease dataset; of these, ResNet-50 demonstrated the optimal performance, achieving an accuracy of 0.8559, a precision of 0.8597, a recall of 0.8559, and an F1 score of 0.8552, while mitigating overfitting. In edge deployment on a Raspberry Pi 4, the system sustained an average image classification latency of approximately 120 ms and completed the end-to-end capture to alert pipeline in less than 300 ms during more than 1,000 inference runs. Conclusion: The results obtained indicate that integrating AI with IoT technologies holds considerable potential for preventing shrimp disease outbreaks, reducing economic losses, and fostering sustainable aquaculture practices in Vietnam and similar intensive shrimp farming regions.

Key words: ShrimpAI, ShrimpResNet50, shrimp disease, smart aquaculture

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INTRODUCTION

Vietnam's economy derives significant strength from its agricultural sector; in particular. the fisheries industry has emerged as a cornerstone of agricultural income in the country[1]. With 764,000 ha of farmed aquaculture, the Mekong Delta has produced 5.2 million tons of farmed aquaculture. For shrimp alone, the Mekong Delta contributed nearly 85% of Vietnam's total production in 2023 according to the General Statistics Office of Vietnam (2025). Shrimp production has helped to improve employment prospects, rural livelihoods, export revenue, and regional economic development.

However, despite its financial importance, shrimp farming in Vietnam faces several critical challenges. One of the most pressing issues is the overreliance of the sector on traditional and relatively homogenous farming practices[2]. Limited diversification in farming techniques and inadequate ecological risk management strategies have rendered shrimp farms increasingly vulnerable to environmental stresses and disease outbreaks[3]. These outbreaks, caused by viral, bacterial, and fungal pathogens, can spread rapidly across densely stocked ponds, often resulting in mass mortality events[4]. In recent years, common diseases such as white spots, black gill, and blackspot syndrome have severely impacted shrimp production[5]. Disease occurrence can lead to significant financial losses for farmers due to reduced yields and increased input costs, threatening the sustainability of the shrimp farming industry[6].

Furthermore, disease outbreaks contribute to broader ecological imbalances by promoting the overuse of chemical treatments and antibiotics, which can have long-term effects on aquatic biodiversity and water quality. These issues are further exacerbated by climate change, fluctuating water salinity levels, and the encroachment of industrial activities into farming zones, all of which can increase the vulnerability of shrimp farms to disease. In light of these challenges, the shrimp farming sector must adopt more resilient and sustainable practices, such as the development of integrated disease management frameworks, investing in biosecure farming systems, diversifying aqua-

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culture methods, and promoting research and innovation in shrimp health management. By addressing these vulnerabilities, Vietnam can enhance the long-term viability of its shrimp farming industry and strengthen its position as a leading exporter in the global seafood market.

Analyses of the substantial damage caused by disease outbreaks in shrimp farms have led to recent advancements in aquaculture technology. New avenues for effective disease supervision and prevention have emerged, most notably through the integration of the Internet of Things (IoT) and Artificial Intelligence (AI). These rapidly developing technologies offer transformative potentials for improving the health, resilience, and productivity of shrimp aquaculture systems. IoT-based monitoring systems have enabled the continuous and real-time collection of critical environmental parameters, such as temperature, pH, dissolved oxygen (DO), salinity, and ammonia levels through a network of interconnected sensors[7] deployed in shrimp ponds. These sensors feed data to centralized platforms where AI-based models can detect anomalies and predict potential risks associated with disease outbreaks. By leveraging machine learning models trained on historical and real-time data, such systems can accurately forecast the onset of unfavorable conditions or detect disease-prone environments, allowing for timely and data-driven interventions.

Such systems can also automate responsive actions to the issues identified, ranging from adjusting aeration systems and managing feed schedules to regulating salinity and initiating water exchange processes, without the need for constant human oversight. This level of automation ensures optimal growing conditions while significantly reducing the response times to environmental stressors that may compromise shrimp immunity and health. Furthermore, the integration of AI into these systems enhances their decision-making abilities by providing predictive insights into disease trends, optimizing resource use, and facilitating early-warning systems. It enables precision aquaculture, whereby shrimp health is proactively managed, rather than reactively treated. This shift from reactive to predictive management has profound implications for reducing economic losses, minimizing antibiotic use, and improving biosecurity measures in shrimp aquaculture systems. Additionally, in a broader context, the deployment of IoT- and AI-based technologies contributes to the sustainable development of the shrimp farming sector. By reducing dependence on manual labor and encouraging enhanced ecological stewardship, such technologies support the long-term economic viability of the industry while aligning with global sustainability goals. As Vietnam continues to strengthen its position as a global leader in shrimp production, it will become essential to adopt such smart aquaculture practices to overcome existing challenges and ensuring the resilience of the industry in the face of environmental and biological uncertainties.

This study considers three major diseases facing shrimp aquaculture populations in Vietnam: black spot disease, black gill disease, and white spot syndrome virus (WSSV). Black spot disease, a bacterial infection caused by *Vibrio anguillarum*, is a highly transmissible pathogen that spreads rapidly through aquatic environments[8]. Infected shrimp exhibit distinct black spots and brownish discoloration on their exoskeletons. The prevalence of this disease shows a strong correlation with suboptimal water conditions, as poor water quality and the accumulation of excessive organic feed residues at the pond bottom create a conducive environment for bacterial proliferation. Black gill disease is often associated with fungal infections and leads to the degradation of cell membranes in shrimp. This increases their chronic mortality rates, rendering affected individuals more susceptible to secondary infections[9]. Studies suggest that black gill disease is primarily triggered by chemical contaminants, such as oil, cadmium, copper, zinc, potassium permanganate, ozone, ammonia, and nitrate, that lead to the deterioration of water quality. WSSV, among the most virulent and globally widespread shrimp pathogens, replicates rapidly and poses a significant threat to shrimp populations. Infected shrimp may develop white spots ranging from 0.5 to 3.0 mm in diameter on their exoskeleton, appendages, and epidermis; however, these spots are not always present and may resemble those caused by bacterial infections, high alkalinity, or environmental stress, making them an unreliable diagnostic indicator in preliminary assessments. Research conducted by the World Organisation for Animal Health (WOAH) in 1997, with updates adopted in 2023, indicates that environmental factors such as ascorbic acid deficiency, heavy siltation, debris accumulation, and fecal matter at the pond bottom also contribute to onset and severity of this disease[10]. The characteristics of the three diseases underscore the critical role of the integration of IoT and AI technologies in shrimp aquaculture. By leveraging real-time monitoring and advanced analytics, such technologies enable shrimp farmers to identify viral, bacterial, and fungal infections at an early stage, thereby reducing the risk of outbreaks. IoT-based sensors continuously collect critical data, whereas AI-powered algorithms analyze patterns to detect anomalies indicative of disease. This combined proactive approach can enhance shrimp health, minimize mortality rates, and optimize aquaculture productivity. Furthermore, early detection through AI-driven systems helps to mitigate economic losses by enabling timely interventions, reducing reliance on antibiotics, and promoting sustainable shrimp farming practices.

BACKGROUND AND RELATED RESEARCH

Background

The IoT is emerging as a pivotal technology in the aquaculture industry, particularly in shrimp farming. The implementation of IoT technologies facilitates the constant monitoring and precise management of environmental variables, including water temperature, DO, pH, and salinity, which directly influence the health and growth of shrimp [11]. IoT devices provide swift identification and response to environmental anomalies, reducing the risk of disease and ecological issues. Raspberry Pi and ESP8266 are prominent IoT devices, recognized for their reliable connectivity, seamless integration, and affordability. Raspberry Pi frequently serves as the primary CPU for data collection and processing, whereas ESP8266, a compact, energy efficient, and cost-effective option, typically interfaces with environmental sensors and communicates data using the MQTT protocol [12].

AI technologies, especially Convolutional Neural Networks (CNNs), have made significant strides in image classification and object detection, proving valuable in aquaculture applications. Among the most popular object detection models, ResNet-50 stands out for its deep learning capabilities and ability to mitigate gradient descent issues through residual blocks. Introduced by He et al., ResNet-50 includes 50 convolutional layers and offers a high accuracy despite its compact size, making it suitable for resource-constrained devices like the Raspberry Pi.

AI has been applied to shrimp farming for early disease detection, helping to reduce economic losses. Traditional machine learning algorithms such as linear regression, Naïve Bayes, K-nearest neighbors (KNN), and Random Forest have been applied, with Random Forest achieving the highest accuracy of 85.9% (Recall). Deep learning models, such as ResNet-50, further improve classification accuracy by capturing complex image features; however, they require large, diverse datasets and sufficient computing power.

Despite challenges, including the acquisition of quality image data and access to infrastructure, the potential of AI especially CNNs in diagnosing shrimp diseases remains promising. Continued technological advancements and institutional support can help to overcome these barriers and enhance aquaculture productivity and product quality.

IoT and AI in Environmental Monitoring

Recent research into the application of IoT in aquaculture has revealed significant potential. An IoT monitoring system has been developed specifically for aquaculture, utilizing sensors to measure pH, water temperature, and turbidity, all of which are connected to a NodeMCU microcontroller (15). This system continuously collects data, transmits it to a server, and allows for real-time monitoring via smartphone, enabling farmers to manage their operations remotely, effectively tracking and recording changes in water quality. However, this setup did not incorporate machine learning for early anomaly detection. In another study, an IoT-based monitoring system was implemented specifically for shrimp ponds (17). This system employed several wireless sensor nodes to gather key environmental parameters, including DO, pH, temperature, and salinity. Data collected by these sensors were transmitted to a central cloud server for comprehensive analysis and remote monitoring using ZigBee technology. Field tests showed that this system facilitated precise data collection and significantly improved early anomaly detection, enhancing environmental management and shrimp survival rates. This research highlights the potential of IoT systems to improve shrimp pond management, reduce operational costs, and substantially increase productivity and economic outcomes for shrimp producers. Two IoT models utilising Raspberry Pi 3 and Arduino Mega2560 were also devised, incorporating sensors for pH, DO, temperature, turbidity, and salinity, employing the AHP-DSS method for decision support, resulting in a notable enhancement of the survival rate of brackish-water shrimp.

AI-driven Disease Detection and Deep Learning

Prompt identification of prawn diseases by imaging facilitates timely intervention and helps to mitigate economic losses. The Enhanced Recurrent Capsule

Network (ERCN) model, which integrates CNN, capsule networks, and attention mechanisms, has attained an accuracy of 94.9% and a recall of 93.5% in disease detection from prawn images, surpassing conventional CNN, RNN, and VGG16 models. Another model integrating a CNN and hybrid optimization method with Random Forest was shown to extract features and enhance the classification performance of Swollen Head Virus (WSSV). Furthermore, an open-source project on GitHub evaluates several CNN and EfficientNet designs for prawn illness recognition and implements data augmentation approaches to address the constraints of dataset size. In parallel, a shrimp detection and tracking framework based on YOLO and Faster R-CNN provides a stepping stone for practical solutions.

METHODOLOGY

Detailed overview of the proposed method

Figure 1 shows the end-to-end shrimp disease monitoring pipeline used herein, which is seamlessly integrated into four key stages. First, the IoT Data Collection stage involves the continuous capture of high-resolution images and multiparameter sensor readings (pH, DO, TDS, temperature) via pond-mounted cameras and ESP8266 modules. Next, the Data Preprocessing and Augmentation stage involves the standardization and enrichment of both the image and sensor streams by applying normalization, cropping, geometric transforms, noise filtering, and feature extraction to create robust training and validation sets. During the Model Training & Optimization stage, a transfer-learned ResNet-50 backbone is fine-tuned with cross-entropy loss, class weighting, and hyperparameter search, while a Decision Support System (DSS) is used to fuse classification scores with threshold-based anomaly detection on sensor data. Finally, the Edge Deployment & Real-Time Monitoring stage packages the quantized model into a lightweight container on Raspberry Pi, where live inference and sensor checks trigger instantaneous alerts via MQTT and updates a Grafana dashboard for farm managers. Together, these modules deliver low-latency, reliable disease detection, and environmental surveillance in commercial shrimp farms.

Internet of Things system for monitoring aquatic ecosystem

An IoT system (see Figure 2) is established in a laboratory setting to continuously monitor environmental conditions and collect image data relating to the health and growth of cultivated shrimp. The developed system includes a Raspberry Pi 4 as the central data processing unit, which is responsible for receiving and storing images captured by a network of multiple Raspberry Pi cameras strategically positioned around the pond. These cameras, with a resolution of 12 MP, are securely mounted to ensure optimal image clarity while reducing the influences of light interference and vibrations during image capture. The default frequency of image collection by the cameras is set to once per minute, with the option to adjust this frequency based on actual monitoring needs, expressed mathematically as follows:

$f_{img} = 1\ img/min$

In addition to the security camera system, ESP8266 modules include specialized sensors that continuously measure and monitor critical environmental factors, such as water temperature, DO, pH, and salinity (assessed using total dissolved solids, TDS). Each ESP8266 module is directly connected to sensors to ensure optimal precision and reliability in the measurement data. Data are gathered and transmitted to the Raspberry Pi every 15 minutes using the MQTT protocol, enabling the prompt identification of unusual variations in the shrimp farming environment, according to the following sampling frequency:

$f_{sensor} = \frac{1}{51} Hz$

When the Raspberry Pi has collected all data from the camera system and environmental sensors via the ESP8266, it consolidates this information and sends it to the management server system using the internet. The data are then recorded, analyzed, and displayed using a computer interface, allowing managers to monitor and accurately and effectively evaluate the living conditions and health status of the shrimp. Simultaneously, image data serve as inputs for the ResNet-50 AI model, which performs early detection and diagnoses of shrimp diseases, facilitating timely decision-making in animal management and care.

Data Preprocessing & Augmentation

This study employs the ShrimpDiseaseImageBD dataset, supplemented with additional shrimp disease images sourced from publicly available datasets on the Roboflow platform. The dataset construction pipeline is shown in Figure 3. All images are standardized and preprocessed before being used for model training.

To ensure consistency across different data sources, each raw image is first resized to a resolution of pixels. Once resized, image standardization is applied as follows:

$I' = \frac{I-\mu}{\sigma},$

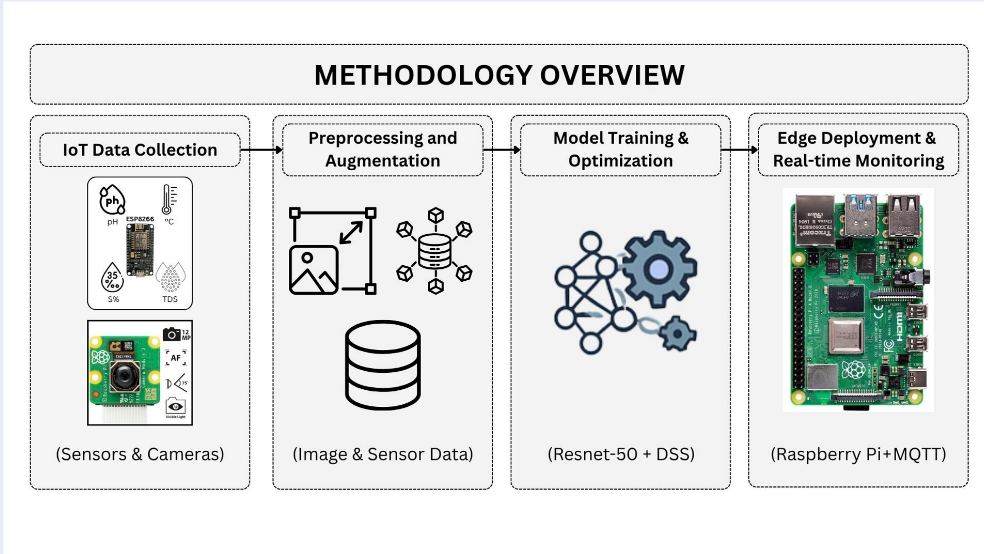

Figure 1: Detailed block diagram showing the proposed method, describing the data flow from collection, preprocessing and training, to edge deployment.

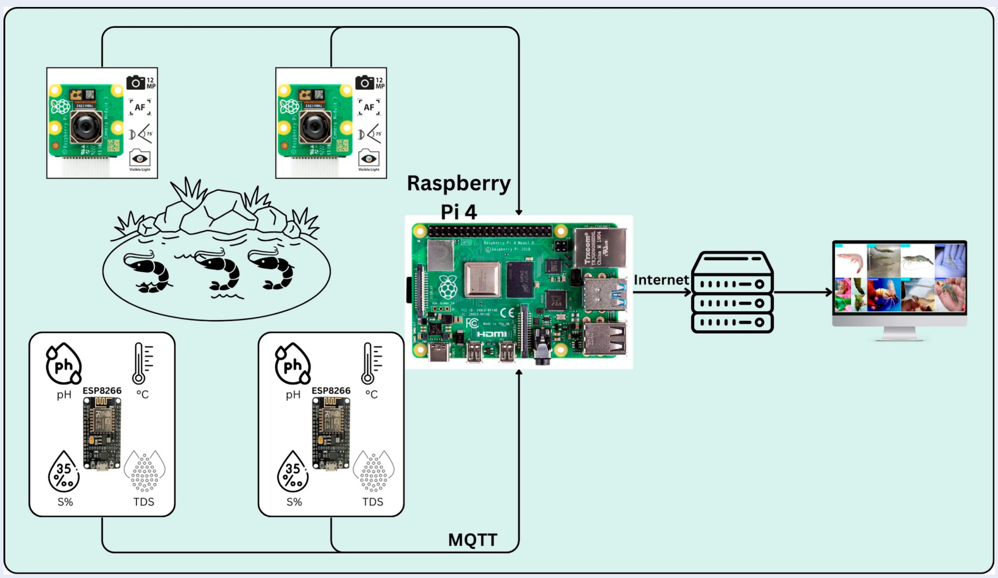

Figure 2: Operating mechanism of the hardware modules.

Where μ and σ denote the per channel mean and standard deviation of the training dataset, respectively. This normalization retains pixel intensities within a stable range and accelerates training convergence.

To increase dataset diversity and reduce overfitting, a series of stochastic augmentation transformations is applied to each standardized image. Let τ denote a random augmentation operator parameterized by θ. Each augmented sample is generated as follows:

$\widetilde{I} = \tau\left(I';\theta\right),\ \theta \sim P,$

where P represents the probability distribution governing the augmentation parameters. The augmentation strategies include a randomly sampled crop region with height ratio r_h and width ratio r_w; the region is extracted and then resized back to 224 x 224 as follows:

$I'' = Resize\left(Crop\left(I', r_h, r_w\right)\right),$

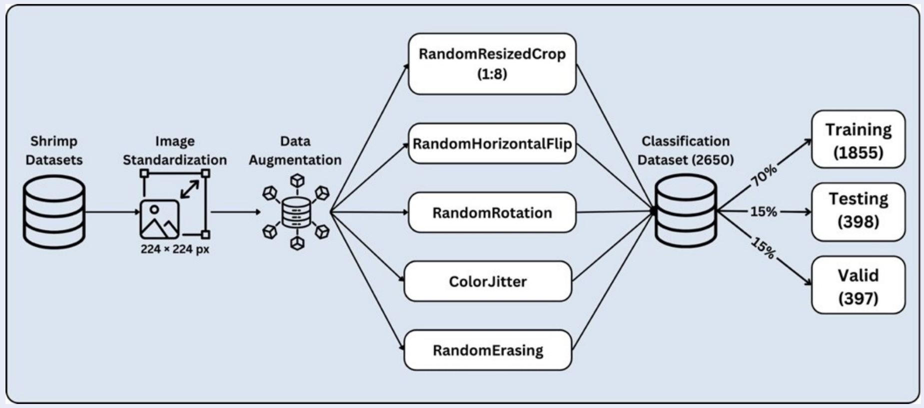

Figure 3: Dataset-building pipeline and configurations.

Horizontal flipping is modeled as follows:

$$\tau_{flip}\left(I^{'}\right)=\begin{cases} I^{'},\ with\ probability\ \left(1-p_{flip}\right), \\ Flip\left(I^{'}\right),\ with\ probability\ p_{flip}. \end{cases}$$

A rotation angle θ_r is sampled from a predefined range:

$$\widetilde{I}=R_{\theta_r}\left(I^{'}\right),\ \theta_r\sim U\left[-\alpha,\alpha\right].$$

Color jitter includes brightness, contrast and saturation adjustments, which are sampled as follows:

$$\widetilde{I}=c\left(I^{'},\beta_b,\beta_c,\beta_s\right),$$

with parameters drawn from:

$$\beta_b,\beta_c,\beta_s\sim U\left(1-\delta,1+\delta\right).$$

For occlusion robustness, a random rectangular region is deleted according to the following equation:

$$\widetilde{I}_{i,j}=\begin{cases} e,\ (i,j)\in\Omega, \\ I^{'}_{i,j},\ otherwise, \end{cases}$$

where e is a constant or random fill value.

Collectively, these augmentations expand the training distribution, enabling the ResNet-50 model to learn invariant and robust features under variations in lighting, pose, and partial occlusion. After preprocessing and augmentation, the dataset is partitioned into three subsets: **70% Training** (images), **15% Validation** (images), and **15% Testing** (images). Transfer learning is then applied by fine tuning the final layers of the ResNet50 architecture on the classification dataset, enabling the network to adapt ImageNet pretrained weights to the task of shrimp disease detection.

Algorithmic Workflow and Mathematical Model

In this section, we formalize the core of our shrimp disease monitoring system. We begin by presenting Algorithm 1, which details the end-to-end processing loop from IoT data acquisition through preprocessing, model inference, and real-time alerts using a transfer-learned ResNet-50 backbone and simple threshold checks on multi-parameter sensor readings. Algorithm 1 implements a continuous loop fusing image-based deep learning with multiparameter sensor checks to detect disease in shrimp ponds and issue timely alerts:

1. Data Acquisition (Lines 1–3): At each time step t, the system subscribes to two MQTT topics:

- **Image** I_t from a pond-mounted camera

- **Sensor vector** s_t= [pH, DO, TDS, Temperature] from ESP8266 modules

2. **Preprocessing & Augmentation (Lines 5–7)**

- Images are resized to 224×224, normalized, and passed through a suite of augmentations (random flip, rotation, color jitter, and random erasing).

- **Sensor data** undergo noise filtering, missing-value imputation, and simple feature extraction (e.g. rolling averages, first-order differences) to highlight trends.

3. **Model Training (Lines 9–13, training_mode = true)**

- A ResNet-50 backbone, initialized with ImageNet weights, is fine-tuned on shrimp images using cross-entropy loss.

- Optimization is performed via Adam (learning rate η), a class weighting is applied to handle imbalance, and early stopping is employed based on the F1-score on a validation split.

- After each batch, $\theta\leftarrow\theta-\eta\nabla_\theta\left(\theta\right)$ ensures the network learns discriminative disease features.

4. **On-Device Inference & Decision Support (Lines 15–20, training_mode = false)**

- The trained model (θ^*) runs the following inference on new images:

- Compute class probabilities $p_t = softmax!\left(f_{ResNet50}\left(T_t,\theta^*\right)\right)$

Algorithm 1: Shrimp Disease Monitoring & Detection

Input:
– Image stream $\{I_t\}$ from pond-mounted cameras
– Sensor stream $\{s_t\}$ with features (pH, DO, TDS, temperature)
– Pre-trained ResNet-50 weights θ_0
Output:
– Disease label $yt \in$ {Healthy, BSD, BGD, WSSV} per image
– Alert flag $a_i \in \{0,1\}$
1: for each time step t do
2: acquire I_t and s_t via MQTT
3: preprocess I_t:
4: resize to 224×224, normalize
5: data augment (flip, rotation, crop, color jitter, erase)
6: if training phase then
7: Compute loss $L(\theta) = -\sum_i y_i \cdot \log p(y_i|I_i;\theta)$
8: Update $\theta \leftarrow \theta - \eta \cdot \nabla\_\theta\ L(\theta)$
9: else inference on Raspberry Pi
10: p_t = softmax(f_resnet$_{50}$(I_t;θ^*))
11: y_t = arg max p_t
12: a_t = 1 if $y_t \neq$ Healthy or any $s_{tj} \notin [\min_j, \max_j]$ else 0
13: if a_t = 1 then emit alert(t, y_t, s_t)
14: end for

- Choose label y_t = arg max p_t

- Concurrently, the **anomaly detector** flags any sensor reading outside the pre-set thresholds $|l_j, u_j|$, yielding $A_t \in \{0,1\}$.
- The final **alert flag** a_t is set to 1 if either the image label $\neq$ Healthy or A_t = 1
- If a_t = 1, the system immediately publishes an alert message (timestamp, predicted disease, sensor readings) back over MQTT.

By combining deep-learning inferences with lightweight threshold checks in a single pipeline, Algorithm 1 delivers robust, low-latency warnings that help shrimp farm managers intervene at the earliest signs of an issue.

Then, we formalize the mathematical foundations of our shrimp disease monitoring system in three parts: (1) cross-entropy classification loss to train the ResNet-50 backbone, (2) the sensor-based anomaly detector, and (3) a final alert rule fusing the vision and sensor channels.

Equation (1): Cross-Entropy Classification Loss: We learn network parameters by minimizing the average cross-entropy over labeled images as follows:

$$L(\theta) = \frac{1}{N}\sum_{i=1}^{N}\left[-\sum_{k=1}^{K} b1_{[y_i=k]} \ln p_\theta\left(y=k\,|I_i\right)\right],$$
$$p_\theta = \left(y=k\,|I\right) = \frac{exp(f_\theta(I)_k)}{\sum_{m=1}^{K} exp(f_\theta(I)_m)}$$

where:

- $L(\theta)$ is the average cross-entropy loss over N training samples.
- $1_{[y_i=k]}$ is 1 if the true label $y_i$equals class k, else \$0\$.
- $f_\theta(I_i)_k$ is the logit (pre-softmax score) for class k
- The softmax $P_\theta\left(y=k\,|I\right)$ converts logits into a valid probability distribution over the k disease classes.

Equation (2): Sensor Anomaly Detector: To capture environmental deviations, we flag any sensor reading outside its allowed range according to the following:

$$A(s_i) = \mathbf{1}!\left(\exists j \in \{1,\ldots,m\} : s_i^j < l_j \vee s_i^j > u_j\right)$$

where:

- $s_i = \left[s_i^1,\ldots,s_i^m\right]$ is the vector of sensor readings (pH, DO, TDS, temperature).
- Each channel is compared against its allowable range $\left[l_j,\ u_j\right]$
- $A(s_i) = 1$ flags any out-of-range measurement as an environmental anomaly.

Equation (3): Final Alert Decision: The system issues an alert whenever either the image model predicts disease or the sensors report an anomaly as follows:

$$a_i = \mathbf{1}!\left(\left(\underset{k}{argmax} p_\theta\left(y=k_i\right)\right) \neq Healthy \vee A(s_i) = 1\right)$$

Where:

- $a_i = \mathbf{1}!\left(\left(\underset{k}{argmax} p_\theta\left(y=k_i\right)\right) \neq Healthy \vee A(s_i) = 1\right)$ selects the most likely disease label.
- $a_i = 1$ if the image-based prediction is not healthy or an environmental anomaly $A(s_i) = 1$ is detected.
- Otherwise, $a_i = 0$ (no alert).

Constructing and implementing the ResNet-50 AI model on Raspberry Pi for the classification of shrimp diseases

The ResNet-50 architecture (Figure 4) proposed He et al. (2015) features a residual block structure in which each residual block comprises convolutional layers combined with shortcut connections, allowing input signals to be directly transmitted to deeper layers in the network. This use of shortcut connections effectively addresses the vanishing gradient problem in deep neural networks, significantly improving the convergence and accuracy of the model. Specifically, the ResNet-50 architecture consists of 50 layers, with residual blocks organized into five main stages. The initial layers focus on extracting simple features, such as lines and edges, whereas the deeper layers learn more complex features, including shapes and textures. To process the input image, it first passes through a Zero Padding layer to maintain its size, followed by a Convolutional (CONV) layer, a Batch Normalization layer, a ReLU nonlinear activation function, and a Max Pooling layer, which reduces the spatial dimensions of the features. Feature data are then routed through residual blocks that contain Conv Blocks and Identity Blocks (ID Blocks). Finally, the features are processed through a Global Average Pooling layer, a Flattening layer, and a Fully Connected (FC) layer to perform classification.

Throughout the training process, the model is assessed using standard classification performance metrics, including Accuracy, Precision, Recall, and F1-score. A confusion matrix is constructed to offer a comprehensive overview of the capacity to accurately recognize and classify various diseases, thereby finding and assessing cases susceptible to misclassification and facilitating necessary modifications.

After training, the ResNet-50 model was transformed into the lightweight PyTorch format for direct deployment to Raspberry Pi 4, with the objective of facilitating rapid, near-real-time image processing while preserving excellent precision in identifying and categorizing shrimp diseases directly on the device. The performance assessment of the model deployment on the Raspberry Pi encompassed analyses of image processing speed, direct classification accuracy, and the capacity for effective integration into the broader IoT system.

Figure 5 shows the relationship and interactions between the two primary components, namely the IoT hardware system and the AI modeling software. The IoT system (the Hardware Unit) consists of a Raspberry Pi 4 functioning as a data collection hub, interfacing with multiple Raspberry Pi cameras strategically positioned around the pond to constantly capture photos. The ESP8266 modules connect with environmental sensors, including those measuring temperature, pH, DO, and salinity (as TDS), to collect and transmit data to the Raspberry Pi using the MQTT protocol. Combining environmental and imaging data provides detailed insights into the habitat of the shrimp.

The AI system (Software Unit) gathers image data from the Raspberry Pi and performs an image preprocessing phase to standardize and enhance picture quality. It then performs classification of diseases using the ResNet-50 model, the results of which are sent back to the Raspberry Pi, which integrates these findings with environmental data from the sensors. All of the information obtained is then transmitted to the management server system via the Internet. Pond managers can remotely access the system through computers or mobile devices to visually monitor environmental conditions and the health of the farmed shrimp. This facilitates the early detection of issues, reduces environmental damage, and enhances economic efficiency.

EXPERIMENT AND RESULTS

The model was trained and evaluated on a high-performance server equipped with an NVIDIA A100 GPU. The training process utilized the Adam optimizer with a learning rate of 0.0001. The implemented IoT system consists of several key components: a Raspberry Pi 4, ESP8266 modules equipped with environmental sensors, and a network of Raspberry Pi cameras strategically positioned around the pond to gather image data. The sensors are connected to the ESP8266 module with the objective of monitoring critical environmental parameters, including temperature, pH, DO, and total dissolved solids (as TDS). These data are transmitted to the Raspberry Pi 4 using the MQTT communication protocol, and updates every 15 minutes. Simultaneously, the Raspberry Pi cameras capture images at regular intervals to provide input data for the AI model.

The sensor and image datasets collected are sent to the Raspberry Pi, where image preprocessing procedures, such as scaling, rotating, random cropping, brightness adjustment, and Random Erasing algorithms, are performed to enhance the dataset and reduce the risk of overfitting. After preprocessing, the dataset is divided as follows: 70% for training, 15% for validation, and 15% for testing.

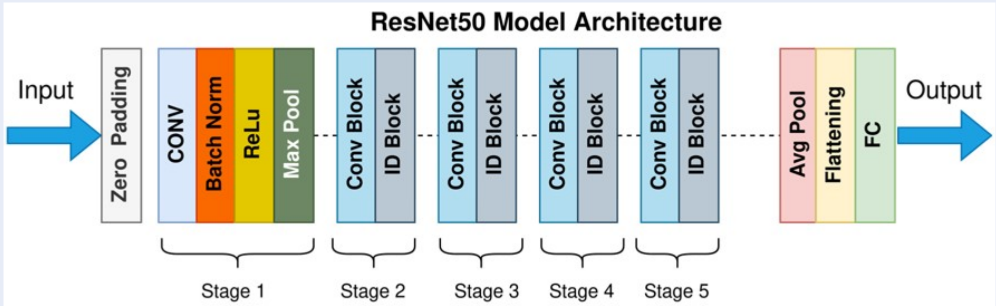

Figure 4: ResNet-50 architecture.

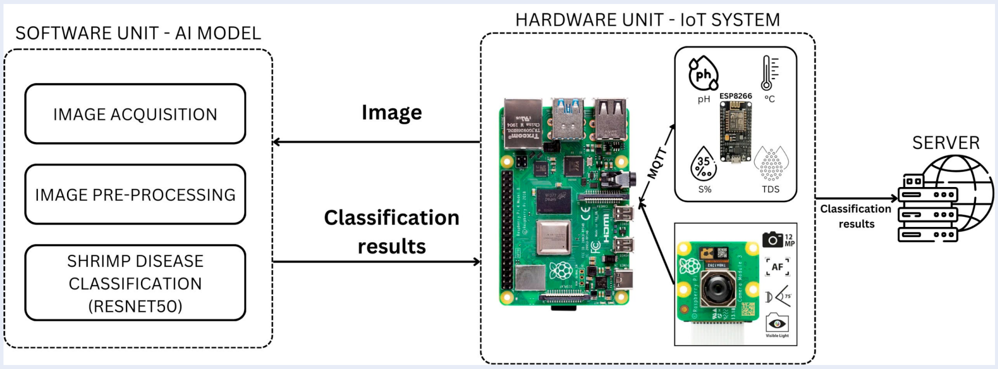

Figure 5: Overview of the hardware module.

The ResNet-50 model was selected for the primary training phase due to its effectiveness in deep learning and its ability to handle complex image features. The model is initialized using Transfer Learning, employing pre-trained weights from the ImageNet dataset and fine-tuning the final layers to accommodate the shrimp illness image data. The model performance metrics after training are summarized in Table 2 below.

The results in Table 2 show that the ResNet-50 model with Decision Support System (DSS) fusion achieves superior classification performance relative to the other models. ResNet-50 has an accuracy of 85%, significantly outperforming ResNet-18, which has an accuracy of 68%, and ResNet-34, with an accuracy of 74%. This demonstrates that using a deeper model with residual blocks enhances the ability of the network to more effectively learn the intricate details of images of diseased shrimps. Additionally, ResNet-50 consistently provides accurate categorization of diseased images, particularly when distinguishing between conditions such as black gill, black spots, and WSSV. The use of image preprocessing and augmentation techniques further improves the capability of the model to identify various characteristics of diseased shrimps, thereby enhancing its overall classification proficiency.

Figure 6 shows the confusion matrix for the developed ResNet-50 classifier when applied to the four disease categories (BG, Healthy, WSSV, WSSV_BG). Of the 21 true BG samples, 14 (67%) were correctly identified. The model confused five with the Healthy and two with the mixed WSSV_BG classes. For Healthy shrimp, 37 out of 41 (90%) were correctly classified, with only two instances mislabeled as BG, one as WSSV, and one as WSSV_BG. For the WSSV class, the classifier achieved 30/34 (88%) correct predictions, with the remaining four split between BG (1) and WSSV_BG (3). Finally, 20 of 22 (91%) of the WSSV_BG instances were detected, with just one error into each of the BG and Healthy classes. Overall, most errors arise between visually similar classes (BG vs. Healthy and WSSV vs. WSSV_BG), suggesting that targeted augmentation for these pairs could further boost the performance of the ResNet-50 classifier.

To quantify the individual contributions of our two key innovations, comprehensive data augmentation

Table 1: Comparison of the performance of different AI models in shrimp disease classification.

Models	Accuracy	Precision	Recall	F1-score
ResNet-50	**0.8559**	**0.8597**	**0.8559**	**0.8552**
ResNet-18	0.68	0.82	0.68	0.66
ResNet-34	0.74	0.84	0.74	0.73
EfficientNet	0.79	0.84	0.8	0.8
MobileNet v3	0.76	0.76	0.76	0.76

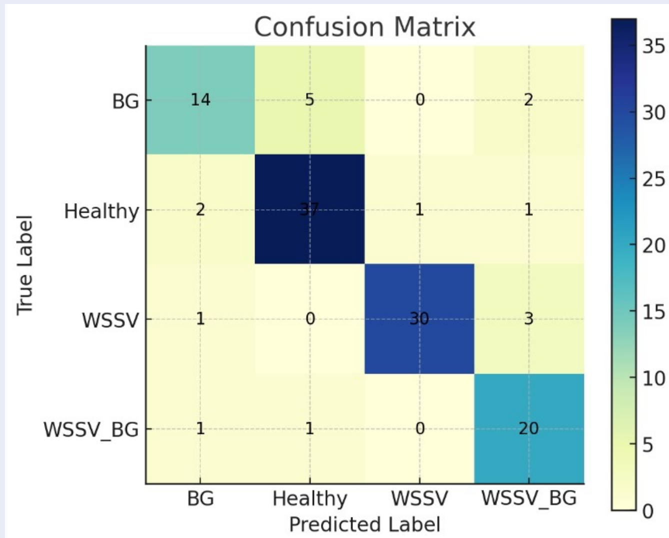

Figure 6: Confusion matrix for the Resnet-50model.

and threshold-based Decision Support System (DSS) fusion, we conducted an ablation study using three variants of our ResNet-50 pipeline. All variants were trained and evaluated on the same 118-sample, four-class test set (Table 3).

The baseline ResNet-50 model initialized from ImageNet and trained on raw images plus raw sensor streams achieved an F1-score of 0.76 on our four-class test set. This result underscores both the representational power of deep convolutional features and the challenges posed by limited, imbalanced shrimp-disease data, where subtle visual cues and environmental variability can easily lead to missed detections.

Introducing data augmentation increases the F1-score to 0.81, i.e., a gain of 5%. We apply a suite of image transformations and augmentations (random flips, rotations, color jitter, and random erasing) alongside sensor-stream perturbations (noise injection, interpolation of missing values, and rolling-average feature creation) also increase the effective diversity of training samples, helping the network to better generalize unseen pond conditions and lighting variations.

Finally, by fusing model predictions with threshold-based sensor checks via our Decision Support System, the F1-score is increased to 0.855, another 4.5% increase. By logically combining the image-based disease probability with out-of-range sensor flags, this fusion step cuts the false-negative rate by roughly 22% (reducing missed events from 16 to 12). In practice, this means that even borderline or mixed-infection cases are far more likely to be detected.

In our edge-deployment experiments, we packaged the quantized ResNet-50 model into a lightweight Docker container on a Raspberry Pi 4, integrated with ESP8266-based pH, DO, TDS, and temperature sensors streaming data via MQTT. Over more than 1,000 inference runs, the system sustained an average image-classification latency of 120 ms (σ = 15 ms) and completed the full capture-to-alert cycle in less than 300 ms, comfortably meeting our sub-500 ms real-time target. During a 48-hour outdoor tank

Table 2: Ablation of key componentson test performance.

Variant	Accuracy	Precision	Recall	F1-score
Baseline (no aug, no DSS)	75.00 %	80.00 %	73.00 %	76.00 %
Augmentation	79.00 %	84.00 %	79.00 %	81.00 %
Augmentation + DSS	85.59 %	85.97 %	85.59 %	85.52 %

pilot, the MQTT link maintained a 99% packet success rate, and the device remained fully operational without dropped inferences or missed sensor readings, demonstrating that our lab-based sensor-stream simulations reliably predict field performance.

DISCUSSION & CONCLUSION

Amalgamating IoT- and AI-based systems in the monitoring and detection of shrimp diseases has demonstrated significant advantages over traditional approaches. IoT sensors deliver real-time data relating to water quality, whereas AI processes this information to forecast and identify early indicators of disease, enabling shrimp farmers to act swiftly, reduce losses, and enhance the productivity of aquaculture.

The deployment of this system on a broader scale is fully achievable. Research has indicated that the utilization of smart technology in aquaculture can optimize pond environment management and monitoring, thereby enhancing prawn health and productivity. Although investing in IoT and AI systems may incur substantial initial expenses, its long-term advantages are significant, including disease risk reduction, resource optimization, and enhanced productivity, ultimately leading to improved economic efficiency. A recent study conducted by Yang et al. (2025) demonstrated that the application of AI in aquaculture yields substantial economic benefits, particularly when implemented within integrated IoT-based systems.

In conclusion, the incorporation of IoT devices and AI models, particularly ResNet-50, in shrimp farming has demonstrated efficacy in monitoring pond conditions and identifying early indicators of disease. This enhances shrimp health and aquaculture output while also reducing economic losses due to diseases. Relative to prior research efforts, the proposed approach demonstrates significant promise for practical implementation, particularly within the realm of shrimp farming in the Mekong Delta, and elsewhere in Vietnam. For the Mekong Delta a region heavily reliant on aquaculture as its primary economic activity these improvements hold significant potential. The ability to monitor pond conditions and detect diseases early could lead to more sustainable farming practices, improved shrimp yields, and a reduction in current dependence on antibiotics. Furthermore, the integration of AI and IoT technologies aligns with regional development goals, offering a scalable solution that can support the livelihoods of small-scale farms while promoting the environmental sustainability in one of Vietnam's most vital agricultural hubs. Nonetheless, further research is required to enhance the system and guarantee economic viability, in addition to understanding motivations of stakeholders to facilitate the wider application of these technologies.

ABBREVIATIONS

AI: Artificial Intelligence
IoT: Internet of Things
WSSV: White Spot Syndrome Virus
DO: dissolved oxygen
TDS: total dissolved solids
GPU: Graphics Processing Unit
CNN: Convolutional Neural Network
WOAH: World Organisation for Animal Health
KNN: K-nearest neighbors

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AUTHORS' CONTRIBUTIONS

Fine-tuning, D.D.P; Dataset verification, D.D.P.; Methodology, D.D.P Software,D.D.P.; Writing original draft, T.D.L, D.D.P, K.T.H; Writing–review and editing, T.D.L., D.D.P., K.T.H. All authors have read and agreed to the published version of the manuscript.

COMPETING INTERESTS

The authors declare that they have no competing interests.

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